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An Explainable Multi-Output Learning Framework for Biosensor-Based User Interaction Analysis

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ABSTRACT

The growing emphasis on user-centered product design has increased the demand for objective and automated approaches to evaluate user satisfaction. Conventional assessment methods, including manual surveys and subjective feedback, are often time-consuming, prone to bias, and incapable of providing real-time insights into user experience. To address these limitations, this study presents a Machine Learning (ML)-based framework for predicting user satisfaction using biosensor data. Baseline models, including Decision Tree (DT), Extra Trees (ET), Linear, and Gradient Boosting (GB), are evaluated within the Classification and Regression Trees (CART) framework. To improve predictive performance, the proposed approach integrates Adaptive Boosting (AB) with CART, enhancing both classification and regression capabilities. The framework simultaneously performs interaction duration prediction as a regression task and user satisfaction classification into High and Medium categories. Experimental evaluation demonstrates that the proposed AB-enhanced CART framework achieves superior predictive performance by improving classification accuracy while reducing regression error compared with baseline models. The developed framework provides a scalable and interpretable solution for real-time user satisfaction assessment, enabling designers, manufacturers, and product developers to analyse user interactions more effectively and support the development of user-centric products and interactive systems.

Keywords: Biosensor Data, User Satisfaction Prediction, Adaptive Boosting, Classification and Regression Trees (CART), Ensemble Learning.

1. INTRODUCTION

The rapid advancement of sensing technologies has significantly expanded the application of biosensors across healthcare, environmental monitoring, smart manufacturing, and human–computer interaction. Biosensors are analytical devices that integrate biological recognition elements with transducers to detect physiological or biochemical changes and convert them into measurable electrical signals. Their high sensitivity, portability, and real-time sensing capabilities have made them valuable tools for acquiring objective physiological information in a wide range of application domains [1]. Recent developments in wearable and non-invasive biosensors have enabled continuous monitoring of physiological signals, providing valuable insights into users' cognitive, emotional, and behavioural states during product interaction. Physiological signals obtained from Electroencephalography (EEG), Electromyography (EMG), and Electrodermal Activity (EDA) provide objective measurements of user responses that cannot be reliably captured through conventional evaluation methods. Unlike questionnaires, interviews, and manual surveys, biosensor-based approaches enable continuous and real-time assessment while minimizing subjective bias, thereby improving the reliability of user experience evaluation [2], [3] The increasing emphasis on user-cantered product design has created a growing demand for intelligent systems capable of accurately predicting user satisfaction from physiological responses. User satisfaction is influenced by multiple cognitive, emotional, and behavioural factors that exhibit complex nonlinear relationships. Conventional ML algorithms, including DT, ET, LR, and GB, provide effective baseline performance for prediction tasks; however, they often struggle to model high-dimensional biosensor data and complex feature interactions. These limitations reduce predictive accuracy and restrict their ability to generalize across diverse user interaction scenarios [4], [5]. Recent advances in ensemble learning have demonstrated considerable potential for improving predictive performance by combining multiple weak learners into a robust predictive framework. AB enhances tree-based learning by iteratively emphasizing misclassified samples and reducing prediction errors, thereby improving both classification and regression performance while preserving model interpretability. Such characteristics make ensemble learning particularly suitable for analysing complex physiological data collected during user interactions.

2. LITERATURE SURVEY

Sobhan, et al. [6] reviewed recent advancements in biosensor- and Internet of Things (IoT)-enabled smart food packaging for improving food safety and quality monitoring. The study highlighted the integration of biosensors with cloud-based IoT platforms for real-time data acquisition, storage, and analysis while discussing challenges related to data privacy, security, and regulatory compliance. The review emphasized future research directions for developing intelligent and secure food monitoring systems. Cosme, et al. [7] investigated predictive modelling techniques for evaluating wine aroma and quality by integrating analytical sensing methods, including gas chromatography and near-infrared spectroscopy, with ML models such as Partial Least Squares Regression (PLSR) and neural networks. The proposed approaches enabled accurate prediction of aroma characteristics and quality traits while supporting real-time quality monitoring. The study also identified the alignment between instrumental measurements and human sensory perception as an important research challenge. Islam, et al. [8] presented a systematic review of deep learning techniques for biosensing applications in healthcare. The review analysed various biosensor modalities, deep learning architectures, and practical healthcare applications while identifying key challenges related to data quality, model selection, and real-world deployment. Future research directions were outlined to improve the reliability and scalability of intelligent biosensing systems.

Tsolakidis et al. [9] reviewed recent developments in data-driven technologies for personalized nutrition using the PRISMA methodology. The study analysed research published between 2021 and 2024, focusing on data collection technologies, predictive analytics, and personalized dietary recommendations. The review highlighted current research challenges and emphasized the growing role of intelligent data-driven systems in precision nutrition. Vo, et al. [10] reviewed recent advances in biosensor technologies for intelligent wound management. The study discussed flexible electronic sensors, electrochemical platforms, and colorimetric sensing systems integrated with AI, smartphone-based analytics, and IoT connectivity for real-time wound monitoring. The review also highlighted self-powered biosensors and closed-loop therapeutic systems as promising solutions for personalized healthcare and telemedicine applications. Chen, et al. [11] examined the role of intelligent biosensors within the Food Safety 4.0 paradigm. The study demonstrated how biosensor technologies combined with predictive analytics enable real-time monitoring, enhanced traceability, and proactive risk management throughout the food supply chain, thereby improving food safety and quality assurance.

Vanaraj, et al. [12] reviewed bio-inspired sensing technologies, including electronic nose and electronic tongue systems, for food quality assessment. By combining sensor arrays with AI-based pattern recognition techniques, these

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systems enabled rapid, non-destructive, and high-throughput analysis for freshness evaluation, spoilage detection, adulteration identification, and beverage authentication across various food products. Yee, et al. [13] reviewed emerging smart fermentation technologies supporting Industry 4.0 and sustainable manufacturing. The study emphasized modular system architectures, scalable sensing platforms, and open-source innovation while highlighting the role of intelligent fermentation technologies in preserving microbial biodiversity and promoting environmentally sustainable industrial development.

Yuxin, et al. [14] proposed an extended Technology Acceptance Model (TAM) integrating biomimetic principles and AI-driven functionalities for wearable technologies. The framework incorporated security and privacy considerations to improve user acceptance while providing new directions for intelligent wearable devices and biomimetic robotics. Madrid, et al. [15] reviewed the current state of smartphone-based biosensor technologies and analysed their progression from laboratory research to commercial deployment. The study identified technical limitations, technology transfer challenges, and end-user adoption barriers that restrict large-scale commercialization, emphasizing the need for improved deployment strategies and user-centered design.

3. PROPOSED METHODOLOGY

This research framework integrates biosensor-based feature extraction with an Adaptive Boosting-enhanced CART model to accurately predict user satisfaction and interaction duration during product usage. The system combines physiological signals with user interaction data to capture both cognitive and behavioural characteristics that influence user experience as shown in Figure 1. A comprehensive preprocessing pipeline, statistical feature extraction, and ensemble learning strategy are employed to improve prediction accuracy and robustness. The framework simultaneously performs classification and regression within a unified architecture, enabling real-time assessment of user satisfaction. Furthermore, a Flask-based deployment platform provides instant prediction and visualization, making the proposed system suitable for practical user-centered product evaluation.

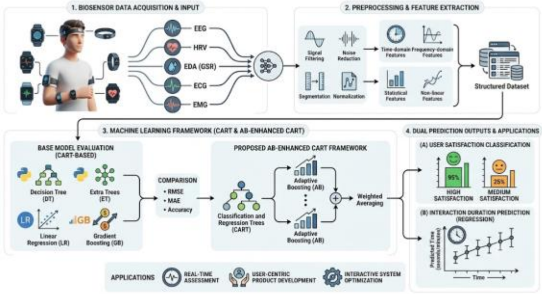

Figure. 1: Workflow for predicting user satisfaction using biosensor data.

Data Acquisition: Physiological signals are collected from biosensors, primarily EEG, during user interaction with products. In addition, behavioural information, including clicks, navigation paths, task completion time, and demographic attributes such as age, gender, and product type, is recorded to construct a comprehensive dataset representing user interaction.

Data Preprocessing: The acquired biosensor signals are pre-processed to eliminate artifacts caused by eye blinks, muscle movements, and external electrical interference. Missing or inconsistent values are handled using appropriate imputation techniques, while numerical features are normalized. Categorical attributes are transformed using Label Encoding or One-Hot Encoding to ensure compatibility with the predictive models.

Feature Extraction: Statistical features, including mean, standard deviation, minimum, maximum, and median, are extracted from the EEG signals to represent physiological responses effectively. These features are combined with interaction-based metrics to generate a multidimensional feature set for predictive analysis.

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AB-Enhanced CART Model: The extracted features are supplied to the proposed AB-enhanced CART framework. CART serves as the base learner, while AB iteratively improves prediction performance by assigning greater importance to previously misclassified or poorly predicted samples. The framework simultaneously performs regression to estimate interaction duration and classification to predict user satisfaction levels (High and Medium).

Feature Importance Analysis: The inherent feature selection capability of CART is utilized to evaluate the contribution of individual physiological and behavioural attributes. This process identifies the most influential features affecting prediction performance and enhances the interpretability of the proposed framework.

Model Deployment and Real-Time Prediction: The trained models and preprocessing components are deployed using a Flask-based web application. New biosensor and interaction data are processed in real time to generate predictions for interaction duration and user satisfaction. The generated outputs support product designers and developers in evaluating user experience, optimizing product design, and enabling data-driven decision-making.

3.1 Dataset Description

The dataset used in this study comprises user-product interaction records, physiological biosensor (EEG) signals, demographic information, and subjective user feedback. Each record represents a single interaction session and contains both numerical and categorical attributes that support simultaneous classification and regression tasks. The dataset is processed through the following stages.

Demographic Data Collection: Demographic attributes, including Age and Gender, are collected for each participant. These features provide user-specific information that helps analyse variations in satisfaction and interaction behaviour across different user groups.

Product and Context Information: Product-related information, including Product Type and Cultural Element ID, is recorded to capture the characteristics and contextual factors associated with each product. These attributes enable the model to learn how different products influence user experience.

Emotional State Acquisition: The emotional state of each participant is represented using the Pleasure Arousal Dominance (PAD) model. Three continuous features such as PAD Pleasure, PAD Arousal, and PAD Dominance are included to quantify the user's affective response during product interaction.

User Interaction and Feedback Collection: Behavioural information is collected through user interaction logs, including User Feedback Satisfaction, Interaction Frequency, and Interaction Duration. The interaction duration is converted from its original string representation into numerical seconds, providing a continuous feature for regression analysis.

EEG Signal Acquisition and Feature Extraction: Raw EEG signals are recorded during product interaction and stored as structured arrays. To transform the physiological signals into meaningful ML inputs, statistical features including mean, standard deviation, minimum, maximum, and median are extracted from each EEG recording. These features capture the cognitive and emotional responses of users throughout the interaction.

Data Preprocessing: Before model training, categorical attributes such as Gender and Product Type are converted into numerical representations using encoding techniques. Numerical features are standardized using Standard Scaler to ensure consistent feature scaling, while missing or inconsistent values are appropriately handled to improve data quality.

Target Variable Preparation: The processed dataset supports both classification and regression tasks. User Satisfaction serves as the

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classification target by categorizing users into satisfaction levels, whereas Interaction Duration (Seconds) serves as the regression target for estimating the time users spend interacting with a product. This dual-target structure enables the proposed framework to perform simultaneous user satisfaction classification and interaction duration prediction.

4. Results and Description

The performance of the proposed Adaptive Boosting-enhanced CART framework is evaluated using both classification and regression metrics to assess its effectiveness in predicting user satisfaction and interaction duration. Comparative experiments are conducted against baseline ML models, including DT, ET, LR, and GB, using the same pre-processed dataset. Performance is analysed in terms of prediction accuracy, precision, recall, F1-score, regression error, and computational efficiency. The experimental results demonstrate the capability of the proposed framework to effectively model complex relationships between physiological signals and user interaction behaviour. A detailed analysis of the obtained results confirms the superiority of the proposed approach for real-time user satisfaction assessment and interaction duration prediction.

Figure 2 shows that the AB algorithm in Target Classification achieves perfect metrics: Accuracy 1.0, Precision 1.0, Recall 1.0, and F1 Score 1.0, indicating possible overfitting or ideal test conditions. The Confusion Matrix shows 29 correct High Satisfaction, 0 errors, and 19 correct Medium Satisfaction with no misclassifications. The Classification Report confirms perfection with both classes having Precision 1.000, Recall 1.000, F1-Score 1.000, and supports 29.0 and 19.0 respectively. Macro averages are all 1.000, making AB the top performer for predicting user satisfaction levels from biosensor data in this analysis.

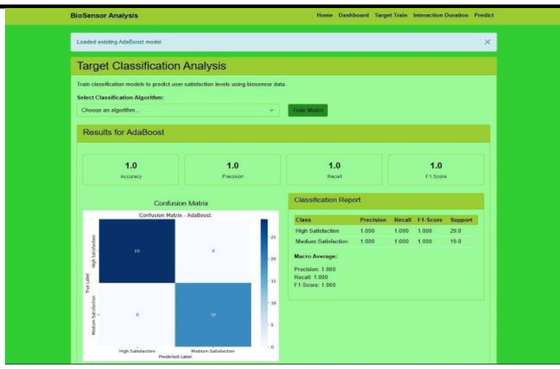

Figure. 2: Target classification analysis AB for biosensor analysis

Figure 3 displays interface presents Interaction Duration Regression Analysis with a loaded AB model for predicting duration using biosensor data. It includes a dropdown for algorithm selection and a "Train Model" button. Results display MAE 0.0, MSE 0.0, RMSE 0.0, and R² Score 1.0, indicating a perfect fit. The Scatter Plot of True vs Predicted Values shows points perfectly aligned on a red diagonal line from (110,110) to (180,180). The layout uses a green background with navigation options like Dashboard, Target Train, and Predict.

Figure. 3: Interaction duration regression analysis –AB for biosensor analysis

Figure 4 allows users to make predictions using trained models for user satisfaction and interaction duration with new data under the "Single Prediction" tab. Input fields include Age (25), Gender (Male), Cultural Element ID (1), Product Type (Chair), EEG Data (JSON array), PAD values (Pleasure 0.6, Arousal 0.4, Dominance 0.7), User Feedback (4.5), and Interaction Frequency (3). After clicking "Predict," results show Classification (Target) predictions: DT (Medium), Logistic (Medium),

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ET (Medium), GB (High), AB (High); Regression (Duration) predicts 120.1s to 123.6s across algorithms. The interface is green-themed with navigation links.

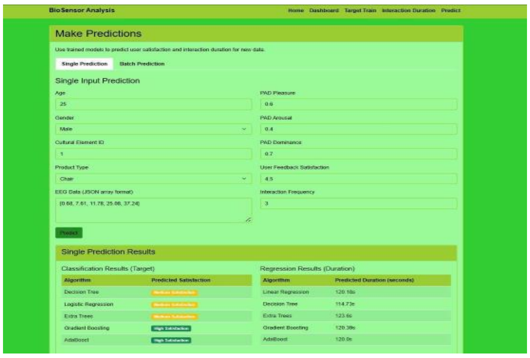

Figure. 4: Make predictions single prediction for biosensor analysis.

Figure 5 shows that facilitates batch predictions from a CSV file under the "Batch Prediction" tab, using trained models for satisfaction and duration. Users upload a CSV file, with a note that it should exclude target columns and follow a specified format including Age, Gender, Cultural Element ID, Product Type, EEG Data, PAD, User Feedback, Satisfaction, Interaction Frequency. Expected CSV format details are provided, with EEG data in JSON array format. Results display Classification (Target) and Regression (Duration) predictions for uploaded data, with algorithms like DT and AB listed. The layout features a green theme and navigation options.

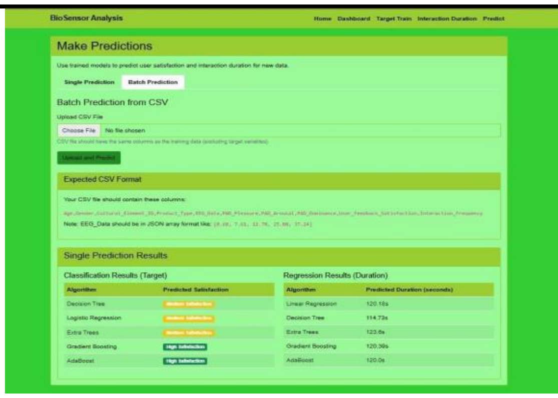

Figure. 5: Make predictions batch prediction for biosensor analysis

Table 1 presents the performance comparison of five classification models such as DT, Linear, ET, GB, and AB based on their accuracy, precision, recall, and F1-score. Among the models, AB achieves perfect performance, scoring 1.0000 across all metrics, indicating exceptionally strong predictive capability on the given dataset. Linear and ET also show competitive and identical results, with accuracies of 0.7292 and balanced precision, recall, and F1-scores around 0.83 and 0.72, reflecting stable classification behaviour. The DT model performs moderately with an accuracy of 0.5625, while GB shows relatively lower precision but acceptable recall. The table highlights significant variation across models, emphasizing AB as the highest-performing classifier in this evaluation.

Table. 1: Comparison of classification models

Model	Accuracy	Precision	Recall	F1 Score
DT	0.5625	0.7922	0.5625	0.5162
Linear	0.7292	0.8392	0.7292	0.7246
ET	0.7292	0.8392	0.7292	0.7246
GB	0.6042	0.3650	0.6042	0.4551
AB	1.0000	1.0000	1.0000	1.0000

Table 2 compares the performance of five regression models such as DT, Linear, ET, GB, and AB using MAE, MSE, RMSE, and R^2 Score as evaluation metrics. The results indicate that Linear Regression and AB deliver perfect predictive performance, achieving zero error across MAE, MSE, and RMSE, along with an R^2 score of 1.0000. GB also performs exceptionally well, with low error values (MAE = 1.7054, RMSE = 2.0177) and a high R^2 score of 0.9927, indicating strong predictive accuracy. The DT model shows moderate performance with slightly higher errors but still maintains a high R^2 value of 0.9791. In contrast,

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ET exhibits considerably larger errors (MAE = 11.8983, RMSE = 12.9585) and the lowest R^2 score of 0.6998, indicating weaker fit compared to other models. Overall, the table highlights large performance differences, with Linear Regression and AB emerging as the most accurate regression models for predicting interaction duration.

Table. 2: Comparison of regression models

Model	MAE	MSE	RMSE	R^2 Score
DT	2.3142	11.7170	3.4230	0.9791
Linear	0.0000	0.0000	0.0000	1.0000
ET	11.8983	167.9224	12.9585	0.6998
GB	1.7054	4.0712	2.0177	0.9927
AB	0.0000	0.0000	0.0000	1.0000

CONCLUSION

The Biosensor Analysis platform effectively utilizes machine learning algorithms to analyse biosensor data for predicting user satisfaction levels and interaction durations in product interactions, incorporating features like EEG data, PAD psychological metrics, and demographic details from a dataset of 240 samples. Classification models such as DT, Linear, and ET achieved consistent accuracy of 0.7292 with F1 scores around 0.7246, while GB underperformed at 0.6042 accuracy, and AB delivered perfect metrics (1.0 across all), highlighting its superior fit albeit with overfitting concerns. In regression tasks, Linear Regression and AB attained ideal R^2 scores of 1.0 with zero errors, DT scored 0.9791, GB 0.9927, and ET lagged at 0.6998, as visualized through confusion matrices and scatter plots. The intuitive, green-themed web interface supports model training, evaluation, and predictions, proving valuable for user experience insights in biosensor applications. Performance improvements can be realized through hyperparameter optimization using Research to boost weaker models, implementing k-fold cross-validation for better generalization and reduced variance, and advanced feature selection techniques like PCA on EEG data to minimize noise and enhance overall predictive accuracy across all algorithms.

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